Effect of different spatial resolutions of multi-temporal satellite images change detection application

Abstract—**Remote sensing (RS) satellites may provide much information about the land cover at different resolutions that have been utilized in many military and civil purposes. Multi-temporal images Change detection (CD) is one of the RS applications. Images Co-registration is an important step before the change detection process, and although they are geo-referenced to each other they may not have the same spatial resolution. So, prior to the multi-temporal analysis, images should be similar in pixel size. Using optical sensors with different characteristics and resolutions to obtain the same geographical area may cause effects in change detection results. In this paper; Image difference pixel-based change detection technique is proposed, and the effect of the image pixel size on change detection is studied. Two Images of the same area are taken from two different sensors; Worldview2 and Quickbird2 images with "2"m and "2.4"m pixel size are used respectively. The change detection results show that; for "2" m pixel size, the change detection is 0.15 % With regard to "1" m, the change detection is 0.06 % With regard to "2.4" m, and 0.05 % with regard to "4" m pixel size. On the other hand, the change detection results show that, for "2.4" m pixel size, the change detection is 0.09 % With regard to "1" m and 0.015 % With regard to "4" m pixel size.**

Keywords—Remote Sensing; Pixel-based change detection; Resampling; Geometric Correction

I. INTRODUCTION

Pixel is the smallest area unit in a digital image. The size of the pixel is dependent on the sensor type and determines the resolution of the image. In qualitative terms, the resolution is the amount of details that can be observed in an image. The more pixels are included in a remote sensing image of a specific area, the higher the spatial resolution which means the more details can be observed, and vice-versa. Change detection of multi-temporal satellite images is one of the useful research fields in RS applications. There are many challenges on applying multi-temporal imageries change detection to explain the timely changed information on the earth's environment and activities of human [1]. To get these changes in a short period, several change detection methods using different dates of satellite images (typically one image annually). Moreover, although clouds may cover the images partially, the need of cloud-free images will be better in terms of study and application [2-3]. Usually, the aim of the change detection is to show land cover changes that have occurred between two co-registered satellite images taken in the same area at two different times [4].

In general, the change detection algorithms can be classified into two classes; first, the unsupervised classifications based techniques, second the supervised Classification based methods. Unsupervised algorithms are concerned with the natural groups or structures identification within the multispectral images. No earlier information about the study area is needed for this method of change detection. Generally, the unsupervised algorithms get the multi-temporal images as input and a change map that shows changed versus unchanged objects as output. Image difference, Image rationing, vegetable index differencing, change vector analysis, and principal component analysis is some of the well-known unsupervised change detection algorithms. The main drawback of this type of algorithms is the insufficiency of details from-to change information. According to the other type of classification which is the supervised algorithm that uses prior training samples, which have a known identity to classify pixels of unknown identity. Supervised change detection approach compares the classified images on a pixel by pixel basis and extracts the change information [5-6]. The user can also assign the number of classes to the image. Many analysts integrate both of classification processes into one algorithm to generate a final output analysis and classified maps.

An essential stage in all tasks of image analysis such as image fusion and change detection is Image co-registration [7]. Multi-temporal change detection of remote sensing Images is an application which uses a highly accurate Image registration; Images are acquired at different times, taken in the same geographical area and obtained from different sensors. Therefore, detecting the changes between the consecutive images is the purpose [8]. However, it is difficult to perform an accurate registration between two different time images, especially from multi-sensor due to many factors, such as sun angles and conditions of image capturing [1].

Change detection results will be more accurate when the images are taken at the same time and from one sensor if possible, to eliminate any differences due to the amount of the healthy green foliage.

Visual inspection is the first step to detect the changed objects and activities between the co-registered images from two different dates, even if the algorithm which implemented for the change detection process is an Automatic (Campbell, 2011). One of Most image processing tools of change detection visually is to swipe one image over the other or flicker between them and view images side-by-side to detect the changes.

This paper researches the unsupervised change detection Technique through a direct comparison of the two images, in which the analysis of the difference image is the key content. So, we begin in Section 2 by formally defining the main problem and the proposed algorithm of the image difference as a Pixel-based change detection method. Section 3 describes the image processing methodology using preprocessed images, then the image processing algorithm. Section 4 describes an evaluation experiment and discusses the results. Finally, the remainder of the survey gives the conclusion in Section 5. The Algorithm is coded in MATLAB environment.

II. THE CHANGE DETECTION METHOD

The core problem with this paper is as follows. We are given a pair of images of the same scene taken at different times T1, and T2 respectively. The goal is to know how can the spatial resolution (pixel size) of satellite imagery affect the change detection; furthermore, does this effect have a significant impact we should take into account in any application? And consequently, how can we evaluate these answers in terms of cost and processing time. The next subsection describes the proposed algorithm of the change detection.

A. Proposed Algorithm

Let us consider two multispectral images of the same geographical area acquired at two different times taken from two different sensors as shown in Fig. 1. The change detection algorithm is implemented by an unsupervised technique and divided into two main following steps: (1) Pre-processing, This procedure is aimed at rendering the two images similar in both spectral and spatial domains. Including the co-registration step to let the images compared with a pixel by pixel; (2) Change Detection method "Image Difference", such as the univariate image differencing (UID).

III. METHODOLOGY

A. Image Pre-processing

The following subsections describe the preprocessing procedures.

1) Radiometric enhancement

To reduce any of illumination variations between the multi-temporal imagery, radiometric correction is often performed to increase sensitivity to landscape change. Dark Object Subtraction (DOS) is a simple empirical atmospheric correction method for satellite imagery to cancel out the haze component caused by additive scattering from remote sensing data (Chavez Jr, 1988). DOS correction is performed as an automated process which produces corrected multispectral images [16].

In this way, radio-metrically corrected images should appear as if they were acquired by the same sensor and under the same lighting conditions [14]. Even though, absolute radiometric correction is difficult to be implemented in most situations in reality.

2) Spectral Bands Selection

The aim of this step is to select the most informative band subset of the original images to offer better CD performance. Data sets in the study are obtained from two different satellites. First, a WorldView2 of 8-bands imagery with 2-m spatial resolution and the second image is taken from a QuickBird2 of 4-bands imagery with 2.4-m spatial resolution. Three main standard spectral bands (R, G, and B) are selected from the World-View2 and Quick-Bird2 images for the experiment.

3) Resampling

In many cases, we are forced to use multi-temporal images coming from different sensors, so resampling is an important step to rescale an image to each other. The widest method is Nearest Neighbor because of the simplicity and the ability to preserve the original values in the unaltered scene [11]. Resampling is implemented as follows; the WorldView2 image is up-sampled from 2-m to 1-m pixel size and down-sampled to 2.4-m, and 4-m pixel size respectively in different study cases. The QuickBird2 image is up-sampled from 2.4-m to 1-m and 2-m pixel size respectively and down-sampled to 4-m pixel size in different study cases before the image co-registration step.

4) Subset

A subset is generally performed when the image has to be reduced in size or a sample portion of the image has to be taken for performing some analysis. Both images are cropped by coordinates; it is helpful to study only the area of interest (AOI). This is to eliminate any unessential data in the file and also to speed up processing time due to the smaller amount of data.

5) Geometric Correction

Resolution of all images should be as similar as possible to be compared. It is more desirable to select two images acquired by the same sun angle If possible, to control shadows and incident light. The importance of accurate image registration of the multi-date imageries is to avoid any spurious results of change detection due to miss registration (Townshend et al., 1992; Dai and Khorram, 1999; Stow, 1999; Verbyla and Boles, 2000). To ensure that the time series images well aligned [9].

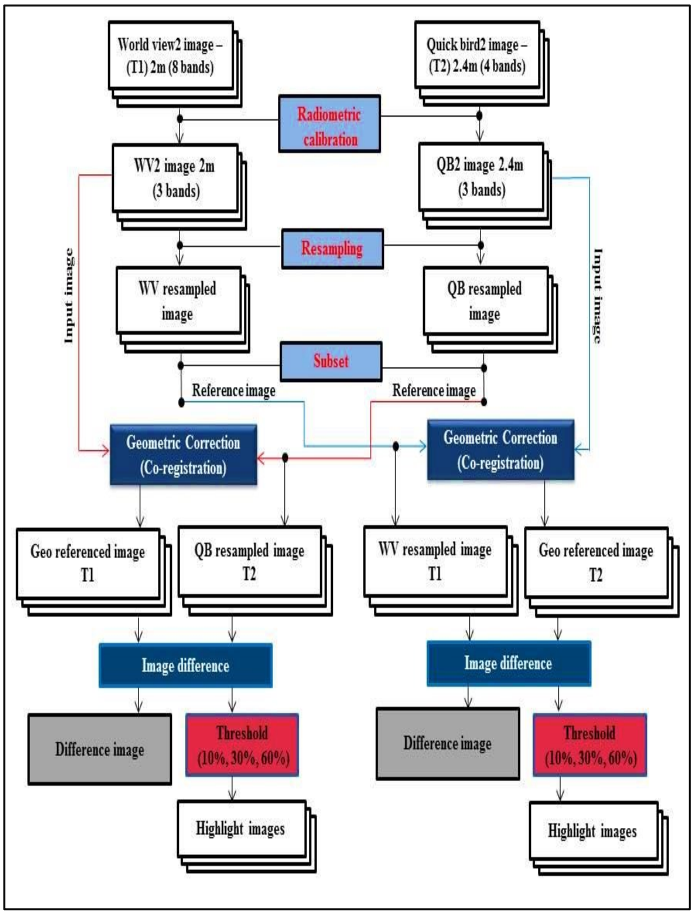


Fig. 1. Flowchart of the proposed change detection algorithm.

Imagery always needs to be geometrically corrected to a map coordinate system to be useful. This is especially true for applications such as change detection; the geometric correction must be highly accurate because any misalignment of features at the same location could render the results useless [7]. One of few techniques to develop compensation approaches for miss-registration effects on image change detection is an ERDAS Auto Sync Workstation which is applied in our work. It uses an automatic point matching algorithm to generate thousands of tie points and produces a mathematical model to tie the images together. The resulting workflows significantly reduce or sometimes completely eliminate manual point collection since it provides more flexibility and tools for visual results inspection and manual digitizing [12].

B. Change Detection Method

1) Image Difference

Early change detection methods were based on the signed difference image as shown in *Fig. 2,* the most obvious algorithm is to simply threshold the difference image [15].

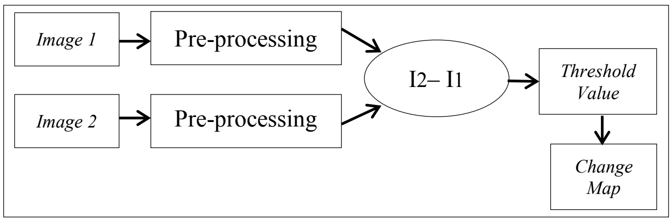


Fig. 2. Block diagram of Image Differencing.

Fig. 3 shows a graphical model of the proposed pixel-based change detection algorithm. Making a model in Spatial Modeler tool by ERDAS Software to implement the image differencing between the two precisely co-registered images that taken from the same scene at times *T1* and *T2* as in (1):

Mathematically,

$$D(x) = I_2(x) - I_1(x) \qquad (1)$$

Where,

I_1 & I_2 = images from time *T1* and *T2*
x = coordinates of each pixel value
D = difference image

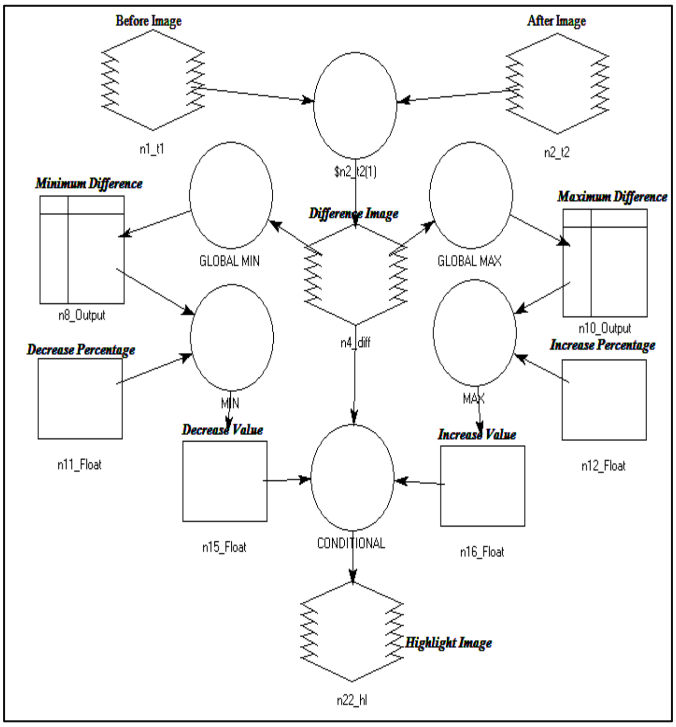


Fig. 3. Graphical model of change detection algorithm.

Unchanged pixels are distributed around the mean (Luetal, 2005), while the changed pixels are distributed in the tails of the distribution curve (Singh, 1989) [10]. Therefore the output image (difference image) is a single band (SB).

Selection of threshold values is up to the expertise of the analyst with a prior knowledge about the scene, Therefore; three suitable threshold levels are chosen to differentiate the changed and the unchanged pixels, a classified image also known as *Highlight image* is the output according to the value of the Threshold Level (TL).

IV. EXPERIMENTAL RESULTS

In this section, data sets that used for experiments are presented. Obviously, if we had conducted the experimentation with multi-temporal images coming from the same sensor we would have reached more comforting results, but we want to underline that, also with low-cost data, it is possible to affect a screening of the changes as illustrated later.

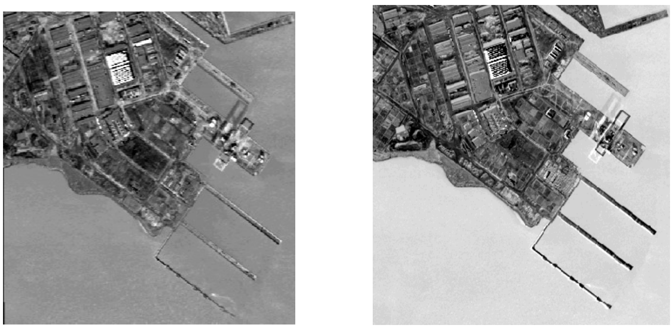
A. Data Set

The data set which used in the experiments are composed Of a test window of (724×729 pixels) of two multispectral images acquired by the WORLDVIEW2 and QUICK BIRD2 satellites with pixel size 2-m at (12-10-2011 T19:15:55) and 2.4-m at (28 -11-2011 T19:48:45) respectively. The two multispectral images are acquired in Oakland, California, Fremont, San Jose, Candlestick Point (San Francisco, California), WGS84 Spheroid Model and Datum, (UTM) projection system, Zone10 (meters) see *Fig.* 4(a) and (b).

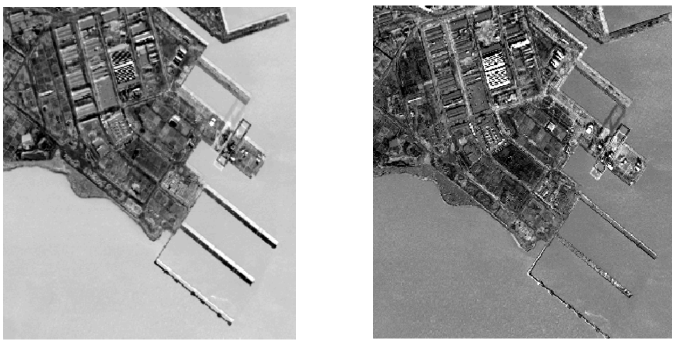
a) Worldview2 image (2m) b) Quick Bird2 image (2.4m).

Fig. 4. The multi-temporal original images.

Two co-registered image dates are subtracted pixel by pixel in the first band to produce a new change image between two dates; The gray values of each band the resultant image show the differences in corresponding pixel values so that, the difference images are illustrated in all cases of pixel sizes respectively as shown in *Fig*. 5(*a*), (*b*), (c) and (d).



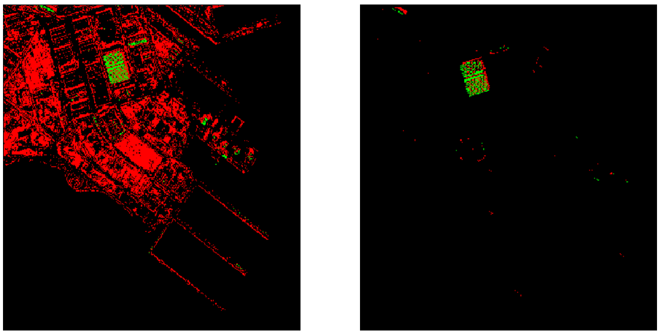
a) Difference image (1 m). b) Difference image (2 m).



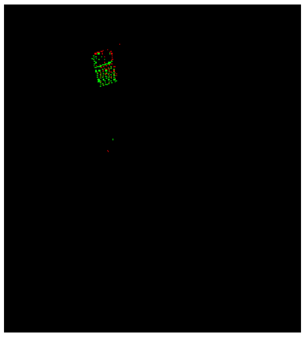
c) Difference image (2.4 m). d) Difference image (4 m).

Fig. 5. The difference (SB) images

According to the previous figure of the proposed model, three threshold levels are applied as percentage values (10%, 30%, and 60 %) in each case as shown in the next figures as follows:

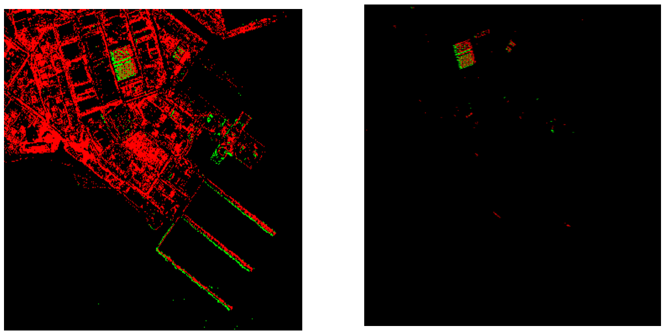


a) Threshold level (10%). b) Threshold level (30%).

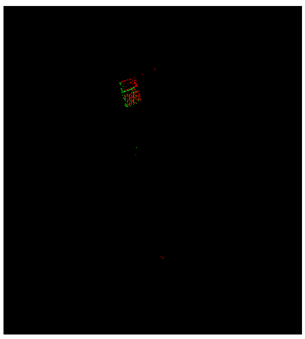


c) Threshold level (60%).

Fig. 6. The highlight (classified) images 1-m.

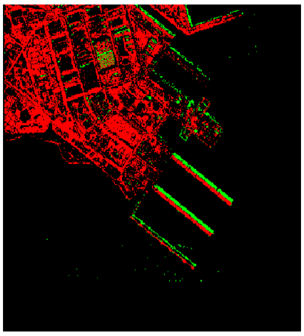


a) Threshold level (10%). b) Threshold level (30%).

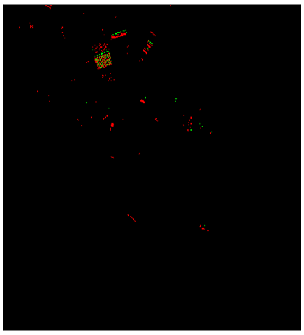


c) Threshold level (60%).

Fig. 7. The highlight (classified) images 2-m.



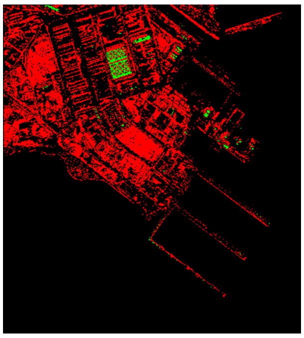
a) Threshold level (10%).



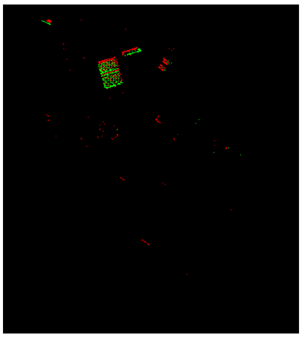
b) Threshold level (30%).

c) Threshold level (60%).

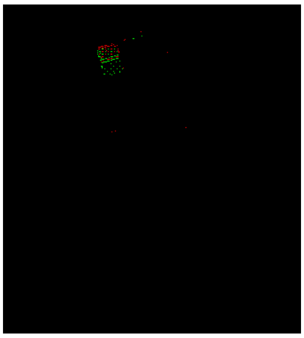
Fig. 8. The highlight (classified) images 2.4-m.



a) Threshold level (10%).



b) Threshold level (30%).



c) Threshold level (60%).

Fig. 9. The highlight (classified) images 4-m.

Each classified image has three classes as follows:

1) Increased pixels in a green color.

2) Decreased pixels in a red color.

3) Background (unchanged pixels) in a black color.

Table 1 gives the results of the image difference of the first spectral band of the two images and illustrates the changed (increased and decreased) pixels at three threshold levels in each case.

TABLE I. COMPARISON BETWEEN THE CHANGE DETECTION IN ALL CASES

TL	**No. of pixels**	**Spatial resolution**			
		Pixel size "1" m	**Pixel size "2" m**	**Pixel size "2.4" m**	**Pixel size "4" m**
10%	*Increased pixels*	11000	3235	2101	768
	Decreased Pixels	310604	89415	68004	22250
30%	*Increased pixels*	5454	1577	956	339
	Decreased Pixels	5204	1652	1151	409
60%	*Increased pixels*	2263	638	314	79
	Decreased Pixels	1407	405	297	63

According to the mathematical concept of the percentage of change of a variable and which it expresses a way to the change. It represents the relative change between the old value and the new one [13]. As shown in table 1, the difference in pixel size in both images in each case has an effect on change detection and illustrated as follows:

At (10%) TL, for instance, The Total No. of the increased pixels of "2" m relative to the "1" m pixel size can be calculated as:

Area of (2m) = 3235× (2 × 2) = 12940 pixels.

Area of (1m) = 11000× (1 × 1) = 11000 pixels.

Hence, The Percentage of the increased pixels between the two images = $\frac{12940 - 11000}{12940}$ = 0.15 %.

The Total No. of the increased pixels of "2" m relative to the "2.4" m pixel size can be calculated as:

Area of (2m) = 3235× (2 × 2) = 12940 pixels.

Area of (1m) = 2101 × (2.4 × 2.4) = 12101.76 pixels.

Hence, The Percentage of the increased pixels between the two images = $\frac{12940 - 12101.76}{12940}$ = 0.06 %.

The Total No. of the increased pixels of "2" m relative to the "4" m pixel size can be calculated as:

Area of (2m) = 3235× (2 × 2) = 12940 pixels.

Area of (1m) = 768 × (4 × 4) = 12288 pixels.

Hence, The Percentage of the increased pixels between the two images = $\frac{12940 - 12288}{12288}$ = 0.05 %.

On the other side according to the second image cases, at (10%) TL, for instance, The Total No. of the increased pixels of “2.4” m relative to the “1” m pixel size can be calculated as:

Area of (2.4m) = 2101× (2.4 × 2.4) = 12101.76 pixels.

Area of (1m) = 11000× (1 × 1) = 11000 pixels.

Hence, The Percentage of the increased pixels between the two images = $\frac{12101.76 - 11000}{12101.76}$ = 0.09 %.

The Total No. of the increased pixels of “2.4” m relative to the “4” m pixel size can be calculated as:

Area of (2.4m) = 2101× (2.4 × 2.4) = 12101.76 pixels.

Area of (4m) = 768 × (4 × 4) = 12288 pixels.

Hence, The Percentage of the increased pixels between the two images = $\frac{|12101.76 - 12288|}{12101.76}$ = 0.015 %.

V. Conclusion

Image differencing is an explicit and simple approach, it is sometimes known as delta change detection and most commonly used method than others. This technique can be applied to multiple bands as a (multivariate image differencing). Atmospheric correction should be applied to compensate for the variation of the illumination conditions. This method just shows whether a change occurred or not and not "what" changed, and hence the performance is poor in urban change detection.

According to the pixel-based change detection analysis, pixel size affects the change detection but to some extent. Although image difference between two different images that taken by two different sensors in different illumination situations may bring out a lot of false signals. The change detection results show that; for “2” m pixel size, the change detection is 0.15 % With regard to “1” m, the change detection is 0.06 % With regard to “2.4” m, and 0.05 % with regard to “4” m pixel size. On the other hand, the change detection results show that, for “2.4” m pixel size, the change detection is 0.09 % With regard to “1” m and 0.015 % With regard to “4” m pixel size.

Through by the results that obtained in all cases, the difference between the percentage values of the changed pixels in several pixel sizes is not big enough, so; It is possible to point out that the implementation of a real change detection between bi-temporal images in some applications may don’t need a high-resolution image, thus low-resolution image may be adequate for many cases of change detection of land cover application and consequently, it will be translated in a lower cost body, lower time for processing and be using these results in decision-making. Our plans for future work include a combination of change detection methods leads to a higher quality change detection results.

REFERENCES

[1] Jianya, Gong, et al. "A review of multi-temporal remote sensing data change detection algorithms." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 37.B7 (2008).

[2] Kennedy, Robert E., Warren B. Cohen, and Todd A. Schroeder. "Trajectory-based change detection for automated characterization of forest disturbance dynamics." Remote Sensing of Environment 110.3 (2007).

[3] Huang, Chengquan, et al. "An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks." Remote Sensing of Environment 114.1 (2010).

[4] Bruzzone, Lorenzo, and Diego F. Prieto. "Automatic analysis of the difference image for unsupervised change detection." IEEE Transactions on Geoscience and Remote sensing 38.3 (2000).

[5] Demir, B., Bovolo, F., & Bruzzone, L. Detection of land-cover transitions in multitemporal remote sensing images with active-learning-based (2012).

[6] Bovolo, Francesca, and Lorenzo Bruzzone. "A theoretical framework for unsupervised change detection based on change vector analysis in the polar domain." IEEE Transactions on Geoscience and Remote Sensing 45.1 (2007).

[7] Zitova Barbara, and Jan Flusser. "Image registration methods: a survey." Image and vision computing 21.11 (2003).

[8] Alqurashi, A. F., & Kumar, L. Investigating the use of remote sensing and GIS techniques to detect land use and land cover change: A review. Advances in Remote Sensing, 2(02), 193 (2013).

[9] Hussain, Masroor, et al. "Change detection from remotely sensed images: From pixel-based to object-based approaches." ISPRS Journal of photogrammetry and remote sensing 80 (2013).

[10] Zhu, Zhe. "Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications." ISPRS Journal of Photogrammetry and Remote Sensing 130 (2017).

[11] Bhabatosh, Chanda. Digital image processing and analysis. PHI Learning Pvt. Ltd., (2011).

[12] ERDAS Imagine Help – Used to figure out how to use the tools within the software (2013).

[13] Bennett, Jeffrey O., William L. Briggs, and Anthony Badalamenti. Using and understanding mathematics: A quantitative reasoning approach. Reading, MA: Pearson Addison Wesley, (2008).

[14] Hall, F. G., et al. "Radiometric rectification: toward a common radiometric response among multidate, multisensor images." Remote Sens. Environ 35 (1991).

[15] Ioan, Ciascai, Ovidiu Donciu, and Pop Septimiu. "Laser based displacement measurements using image processing." Electronics Technology, 30th International Spring Seminar on. IEEE, (2007).

[16] Gilmore, Sean, Ashty Saleem, and Ashraf Dewan. "Effectiveness of DOS (Dark-Object Subtraction) method and water index techniques to map wetlands in a rapidly urbanising megacity with Landsat 8 data." Research@ Locate'15 (2015).